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Trends in wheat yields under representative climate futures: Implications for climate adaptation

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ABSTRACT

Underestimating the impacts of climate change on agricultural production could lead to complacency about the potential adaptation challenges. This study used a Representative Climate Futures (RCF) approach to model projected wheat yields under climate change in Australia. It simulated the range of impacts, resulting from a subset of individual Global Climate Models (GCMs), on wheat production in the major wheat regions of Australia. The study used RCFs that represented 'most-likely', 'best' and 'worst' cases across multiple Representative Concentration pathways (RCPs). Median wheat yields modelled for the South West Australia projected declines between 26% and 38%, under a 'most-likely' case for RCP 4.5 by 2090, and between 41% and 49%, under a 'most-likely' case for RCP 8.5. Median wheat yields declined under RCP 8.5 for the 'most-likely' case across the majority of wheat producing regions, with a range of 1% to 49%. Greater declines were projected under the 'worst' cases of hottest and driest climates. However, the 'best' cases of least warm and wetter climates projected an increase in median wheat yield, a range of 2% to 87%. Variability also changed from the baseline under all projected RCFs and across all regions, with a standard deviation of up to 2.46 t/ha under the 'most likely' case at a site in south-eastern Australia. These likely shifts in the size and reliability of yields, combined with concurrent climate change impacts on other factors, mean that agriculture faces significant adaptation challenges, particularly under some of the 'most-likely' scenarios and all of the 'worst' case scenarios. Further work is required to explore how scenarios in one region relate to those in other regions and thus the overall outcome at the continental scale.

1. Introduction

Australian agriculture has developed to cope with a climate that is highly variable, spatially and temporally. This has influenced the choice of farming systems, management practices, productivity, product quality and costs (Howden et al., 2013). Against a backdrop of longer-term climatic trajectories, the unpredictability of Australia's weather patterns is projected to increase with climate change (CSIRO and Bureau of Meteorology, 2016). While temperatures are projected to increase with climate change, projections in rainfall vary between global climate models (GCMs) (Flato et al., 2013). These changes are projected to vary considerably between regions (CSIRO and Bureau of Meteorology, 2015). Overall, it is highly likely that the agricultural sector will need to increase its level of adaptation if it is to better manage the major uncertainties and other challenges ahead in order to ultimately maintain, or genuinely achieve, more efficient, profitable and sustainable production systems (Stokes and Howden, 2010; Whetton et al., 2012; Vermeulen et al., 2013, Prober et al., 2017).

Many climate change impact studies in agriculture have used either a single GCM (Bassu et al., 2011; Cullen et al., 2009; Anwar et al., 2007) or ensembles of GCMs (Asseng et al., 2013; Vermeulen et al., 2013). These studies incorporated projected climate parameters into agricultural models, which to broadly describe what Vermeulen et al. (2013) call impact approaches. These use statistical or mechanistic models that attach probabilities to possible outcomes under the given range of scenarios. Multi-model ensemble simulations generally provide more robust information than any single model (Randall et al., 2007). However, different GCMs produce different climate projections, presenting a range of plausible future climates. There is considerable disagreement regarding the selection of specific models for future impact

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studies, making it difficult to justify using a reduced sub-set of climate projections (CSIRO and Bureau of Meteorology, 2015).

One approach is to use a small set of best performing GCMs based on their ability to replicate features of the current climate, particularly for specific regions. There are more than 40 Global Circulation Models (GCM) used in the Coupled Model Inter-comparison Project Phase 5 (CMIP5) (CSIRO and Bureau of Meteorology, 2015). The benefits of using a subset selection of GCMs reduces the extraneous computations involved with modelling projected climate change using all of the GCMs used in CMIP5. However, selection can be influenced by bias, leading to inconsistencies across studies and confusion among policymakers (Ruane and McDermid, 2017). Furthermore, the exclusion of GCMs deemed of lower reliability might exclude the consideration of low likelihood, but high impact future regional climates of real significance to adaptation planning. To address these shortcomings, Whetton et al. (2012) developed the Representative Climate Futures (RCF) method in impact and adaptation assessment for the selection of GCMs to represent projected climate change across specified regions. This involved classifying projected changes from the full suite of climate models into classes and assigning relative likelihoods based on the number of climate models falling within those classes (Clarke et al., 2011).

The aim of the present study was to apply the RCF methodology to model the range of climate change impacts across the wheat producing regions of southern Australia, comparing these impacts and variability on future yields between regions and RCFs. The implications of the results for climate change adaptation are discussed.

2. Materials and methods

2.1. Sample sites

The Representative Climate Futures (RCF) approach was modelled at 10 sites within four Natural Resource Management (NRM) regions across southern and eastern Australia. Information on location and agro-ecological zone is presented in Fig. 1 and Table 1. All sites modelled were in the 'Temperate Seasonally Dry Slopes and Plains' agro-ecological zone (Williams et al., 2002), apart from Moree, which was defined as 'sub-humid, subtropical slopes and plains (Williams et al., 2002). Sites were selected on the availability of data and as representative of a region. For example, Charlton was representative of the Murray Basin NRM and Minnipa was representative of the Southern and SW Flatlands (East) NRM. Soil input data for each site was sourced from previous studies by Hunt and Kirkegaard (2011) and Chenu et al. (2011), where they provided input data for multiple sites, including those used in this study, across wheat production areas in Australia.

2.2. Climate data

For each site, historical daily climate data were used for a 31-year baseline period from 1980 to 2010 (SILO database, Jeffrey et al., 2001; http://www.longpaddock.qld.gov.au/silo/). Although the IPCC AR5 used baseline climate data from 1986 to 2005 and centred on the year 1995 (20 years), this study extended this baseline from 1980 to 2010 (31 years with 1995 as the centred year), in order to better capture variability between years for the analysis. Weather data were obtained on a daily time step, with variables consisting of solar radiation (MJ/m2/day), minimum and maximum temperatures (°C), rainfall (mm), evaporation (mm) and vapour pressure (hPa) (Jeffrey et al., 2001). The Representative Concentration Pathways (RCPs) used in this study were sourced from the pathways described in Van Vuuren et al. (2011), being RCP4.5 and RCP8.5. These were selected to represent the highest and lowest (stabilization) impact scenarios.

2.3. Global climate models and the representative climate futures

A set of RCFs was used to describe plausible future climates across the study regions (Whetton et al., 2012). The RCFs formed a typology of selected climate variables (Clarke et al., 2011; Whetton et al., 2012). They were based on a multi-purpose decision-support tool to assist understanding and applying of climate change projections for impact assessment and adaptation planning (Clarke et al., 2011). The RCFs were derived from a web-based tool, hosted by the CSIRO Climate Change in Australia project (www.climatechangeinaustralia.gov.au). They were created in this study via a four step process: the first involving the generation of the RCFs; the second being the examination and application of the model results; the third being the identification of a representative GCM for each key climate future; and the final step involved the application of the results in the impact assessment (Fig. 2).

The individual GCM climate variables consisted of rainfall, solar radiation, maximum and minimum temperature, which corresponded to the inputs required for The Agricultural Production Systems sIMulator (APSIM) model (Keating et al., 2003). The NRM regions selected for analysis were the Southern and SW Flatlands West, the Southern and SW Flatlands East, the Murray Basin and the Central Slopes. The full suite of available GCMs was used and individual GCMs were organised into a 'most likely' case, a 'best' case and a 'worst' case. The 'most likely' case consisted of at least 30% or more of total number of GCMs that were aligned around the changes in relation to the baseline climate. The 'best' case was defined as the climate future resulting in the highest rainfall and 'least-hot'. The 'worst' case was defined as the climate future resulting in the least rainfall and 'most hot' (Whetton et al., 2012). Each GCM was ranked against a multivariate ordering technique according to the mean, minimum and maximum (Kokic et al., 2002). The GCM closest to the multi-model mean of the 'most likely' case was selected, along with the GCMs aligning with the minimum and maximum being selected for the 'best' and 'worst' cases, respectively. The RCF outputs were the smoothed average of the GCM grid cells across each NRM zone. These consisted of monthly percentage changes for rainfall and solar radiation and increases in degrees Celsius for maximum and minimum temperature. These delta change factors were applied across local climate information for each site (Cullen et al., 2009). The year 2090 was used for the analysis, because the climate signal would be strongest under both RCPs. The year 2050 was used as the mid-point of the analysis. Projections under respective GCMs grouped under 'worst', 'most-likely' and 'best' cases for 2090 were assigned the same cases for 2050, irrespective of their respective projections for 2050, so as to keep the GCM selection consistent throughout the analysis.

2.4. Cropping simulations

The cropping systems model APSIM-Wheat (Keating et al., 2003) was used to project the potential effects of the study ensemble on wheat crop productivity at the sample sites (Luo and Kathuria, 2013). APSIM has been validated in several studies that matched modelled yield with observed yield (Asseng et al., 1998, 2004; Probert et al., 1995; Luo et al., 2003). A number of studies have analysed wheat yields and changes under projected climate change for the wheat producing regions used in our study (Hochman et al., 2017), including South Australia (Luo et al., 2005), Victoria (Anwar et al., 2007), southeast Australia (Anwar et al., 2015) and south west Australia (Ludwig and Asseng, 2006).

APSIM contains an array of modules (Keating et al., 2003). The key modules deployed in this analysis were Wheat (wheat crop growth and development), management (setting crop management procedures), Water, Soil Organic Matter, Soil Water (soil water balance), Initial Water (initial water balance), Initial Nitrogen, climate control and daily time step weather data for the period of the simulation. Potential crop water uptake was simulated via relationships with root exploration and extraction potential (Keating et al., 2003). Where water was a limiting factor, above-ground biomass accumulation was the product of available soil water and conversion efficiency in transpiration, which was

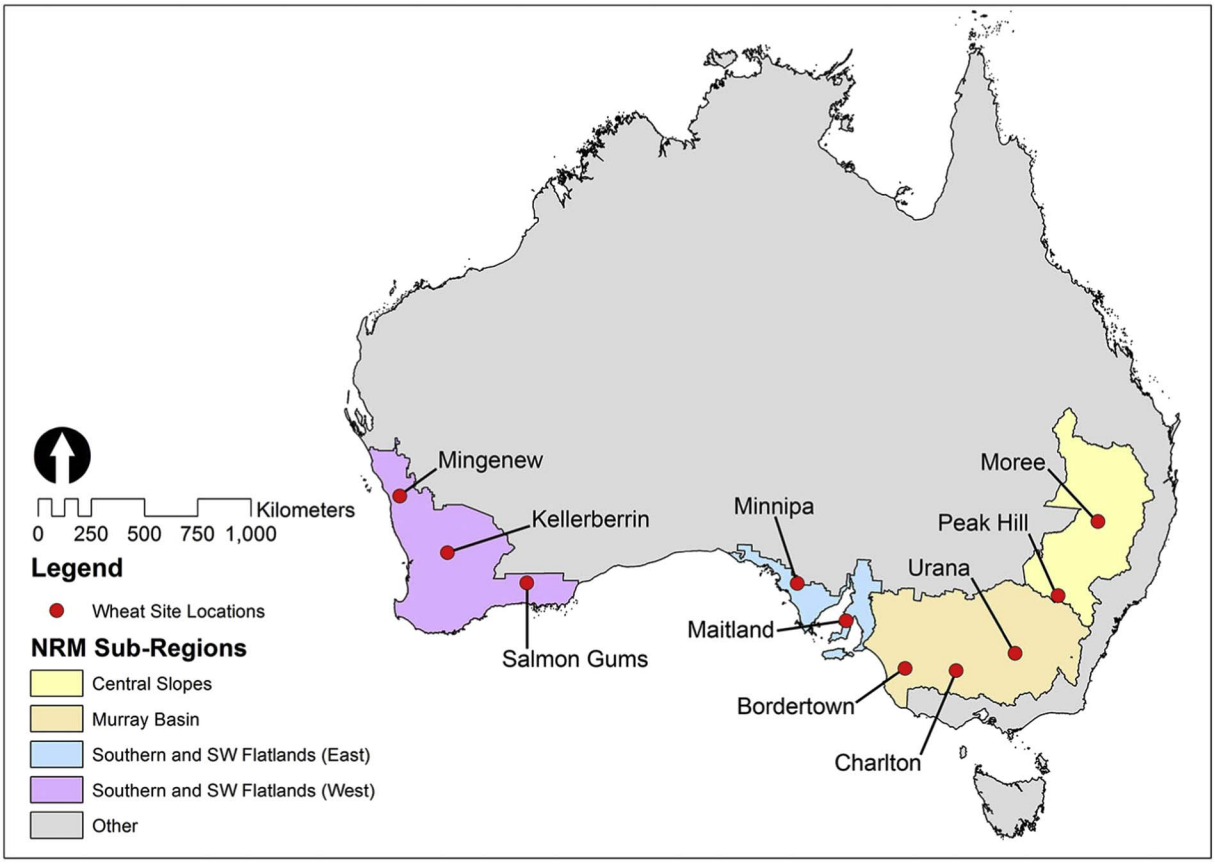

Fig. 1. Location of study sites across Australia.

Table 1
Description of each site modelled, including location, agro-ecological zone.

Location	Lat, Long	Natural Resource Management Zone
Mingenew	− 29.13, 115.39	Southern and SW Flatlands (West)
Kellerberrin	− 31.46, 117.75	Southern and SW Flatlands (West)
Salmon Gums	− 33.48, 122.12	Southern and SW Flatlands (West)
Minnipa	− 32.83, 135.15	Southern and SW Flatlands (East)
Maitland	− 34.34, 137.80	Southern and SW Flatlands (East)
Bordertown	− 36.39, 140.90	Murray Basin
Charlton	− 36.26, 143.21	Murray Basin
Urana	− 35.50, 146.41	Murray Basin
Dubbo	− 32.67, 147.97	Central Slopes
Moree	− 29.50, 149.79	Central Slopes

modified by vapour pressure deficit. Where water was a non-limiting factor, biomass accumulation was the product of intercepted radiation and radiation use efficiency (Bassu et al. 2011). Temperatures and nitrogen deficits also impacted potential growth (Asseng et al., 2011).

The soil parameters were sourced from the APSIM soil database for each site. Modifications to management and soil inputs were sourced from Hunt and Kirkegaard (2012). All sites were modelled as rain fed wheat crops. The soil water balance was simulated using a cascading water balance model (SoilWat). The plant-available water capacity (PAWC) of each soil layer was specified by a crop lower limit and a drained upper limit. Hunt and Kirkegaard (2012) calculated the threshold for water content for soil (represented as the U parameter) and the rate of soil evaporation that indicates change (represented as Cona). The parameter U expressed the mm of evaporation and Cona ($mm/t^{1/2}$) specified the change in cumulative second stage evaporation (Es, mm) against the square root of time. The modified soil default values of U and Cona, according to descriptions of surface texture, were included in the APSIM files (Table 2).

The APSIM manager input was parameterized with sowing (Table 3), management rules and cultivars, as reported by Hunt and Kirkegaard (2012). Crops were sown and established at 150 plants m^2 in all locations in each year of the simulation (Table 3). As this study aimed to detect the effect of climate change on cropping at the sample locations, nitrogen fertiliser was maintained at or near optimum levels by providing 100 kg N ha^{-1} in all simulations, to avoid the confounding effect of N availability on crop yield (Hunt and Kirkegaard, 2012). For the site of Moree, in the sub-humid, subtropical slopes and plains agro-ecological region, N fertiliser rates were higher than those in the Temperate Seasonally Dry Slopes and Plains agro-ecological regions, with 180 kg N ha^{-1} applied to reflect the relative higher rainfall (Chenu et al., 2011).

The APSIM simulations take account of CO_2 fertilisation projected under the RCP8.5 (Riahi et al., 2011) and RCP4.5 (Thomson et al., 2011). For the year 2050, CO_2 atmospheric concentrations were projected to be 486.5 ppm and 540.5 ppm for RCP4.5 and RCP8.5, respectively. For the year 2090, CO_2 atmospheric concentrations were projected to be 538.4 ppm, and 935.9 ppm for RCP4.5 and RCP8.5, respectively.

2.5. Outputs

The APSIM outputs for this study were the annual wheat yields for each of the baseline and projection years. The 31 years for each future climate (2 RCPs being 8.4 and 4.5, with each RCF being 'most likely' case, the 'best' case and 'worst' case scenarios by 10 sites) were sequential years through the model, but analysed as 31 potential instances for each of 2050 and 2090. The RCF tool provided calculations for single projected years, used as the delta change factor. The standard deviation (SD) of the yields was calculated to explore variation between the RCF cases and sites across the 31 potential intances for each

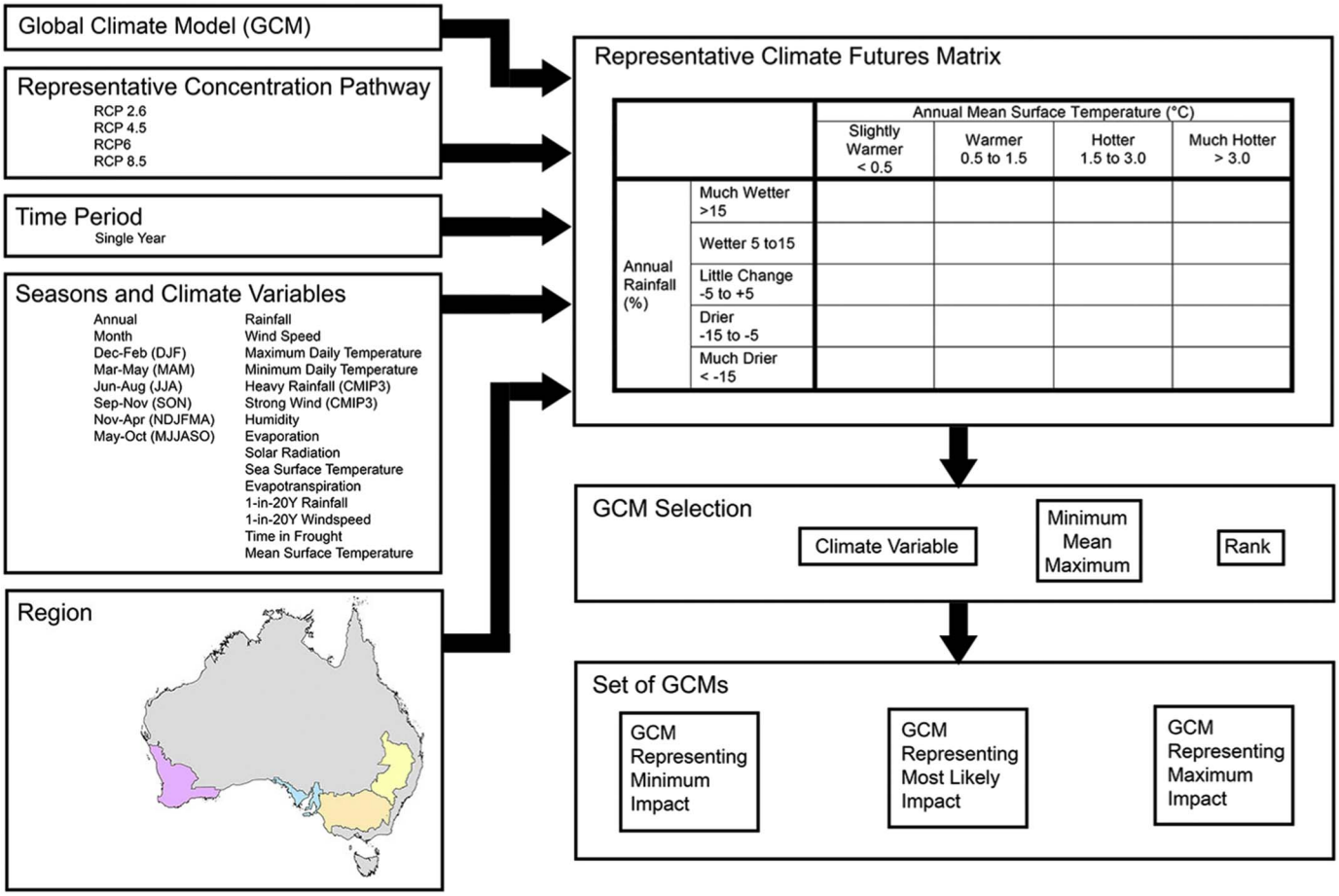

Fig. 2. Outline of the Representative Climate Futures method used in the analysis. Key classifying climate variables consist of rainfall and temperature, RCPs and the projection year. The individual GCM climate variables selected are rainfall, solar radiation, maximum and minimum temperature, which correspond to the inputs required for The Agricultural Production Systems sIMulator (APSIM) model. Subsets of GCMs represent 'cases' around changes in mean temperature and rainfall. Each GCM was ranked against a multivariate ordering technique.

projected year, with comparisons to their respective baselines.

3. Results

3.1. Representative climate futures

The RCF analysis resulted in 8 GCMs selected for RCP 4.5 and 9 GCMs selected for RCP 8.5. All GCMs projected temperature increases for the Year 2090, but varied in their respective rainfall outputs (Tables 4 and 5). Under RCP 4.5 for 2090, the GCMs for all 'worst' cases projected hotter and much drier climates across all the NRMs. The 'most-likely' and 'best' cases were variable across the NRMs. The GCMs projected a drier climate under the 'most-likely' and 'worst' cases for Southern and SW Flatlands West region, being 16% and 33.8%, respectively. However, a 12.7% increase in rainfall was projected for the 'best' case under RCP 4.5 in this region by 2090. Minor reductions in rainfall of 2.5% and 1.2% were projected for the Murray Basin and Southern and SW Flatlands East, respectively. Large reductions in rainfall of 25.4% and 23.5% were projected under RCP 4.5 for both of these regions under their respective 'worst' cases by 2090. The Central Slopes showed rainfall increases of 4.4% and 14.5% for its 'most likely' and 'best' cases, respectively. However, a reduction of 24.6% rainfall was projected with a temperature increase of 3.6 °C under the 'worst' case. The warmest temperature projections under RCP 4.5 were for the Central Slopes, with temperature increases 2.0 °C and 3.6 °C for the 'most likely' and 'worst' cases, respectively. The least warming was

Table 2
Key APSIM parameters for the locations used in the simulation study.
(Based on Hunt and Kirkegaard, 2012).

Location	AP soil file name and no.	PAWC (mm) to depth (m)	U	Cona
Mingenew	Deep Sandy Duplex (Mingenew No428)	135 (2.5)	4	2
Kellerberrin	Deep Loamy Duplex (Kellerberrin No406)	117 (2.1)	4	2
Salmon Gums	Shallow Sandy Duplex (Wittenoom Hills No462)	88 (1.0)	4	2
Minnipa	Red Sandy Clay Loam (Minnipa No310)	202 (1.2)	2	2
Maitland	Sandy loam over clay (Petersville No261)	149 (1.5)	4	4
Bordertown	Dark Grey Medium Clay (Wolseley No344)	253 (1.4)	6	4
Charlton	Clay Loam (Wooroonook No745)	130 (1.0)	6	4
Urana	Sandy Loam over Clay (Rand No212)	157 (1.2)	4	4
Dubbo	Sandy Clay over Clay (Peak Hill No197)	134 (1.5)	6	4
Moree	Black Vertosol (Moree No235)	153	4	2.5

Table 3
SILO Patch point dataset (PDD) station number and sowing parameters for the locations used in the simulation study. (Based on Hunt and Kirkegaard, 2012).

Location	PDD Station Number	Sowing Window	APSIM wheat cultivar maturity
Mingenew	8,088	7 May – 1 June	Early (Wyalkatchem)
Kellerberrin	10,073	7 May – 1 June	Early (Wyalkatchem)
Salmon Gums	12,071	7 May – 1 June	Early (Wyalkatchem)
Minnipa	18,053	1 May – 1 June	Early to Mid (Gladius)
Maitland	22,008	1 May – 1 June	Early to Mid (Gladius)
Bordertown	25,501	7 May – 1 June	Early to Mid (Gladius)
Charlton	80,067	7 May – 1 June	Early to Mid (Yitpi)
Urana	74,110	1 May – 1 June	Early to Mid (Lincoln)
Dubbo	65,012	1 May – 1 June	Mid to late (Gregory)
Moree	53,027	1 May – 1 June	Early to Mid (Hartog)

projected for Southern and SW Flatlands East, with 1.0 °C and 1.6 °C for the 'most likely' and 'worst' cases, respectively.

The 'best' cases under RCP 8.5 projected for 2090 both warmer and wetter climates across all NRMs. In contrast, the 'worst' cases all projected much hotter and much drier climates. The 'most-likely' cases all projected much hotter climates across the NRMs by 2090 under RCP 8.5, but with variable rainfall. Drier and warmer conditions were projected for the 'most likely' and 'worst' cases for the Southern and SW Flatlands West region, Southern and SW Flatlands East region and Central Slopes under RCP 8.5 by 2090. Reductions of 30% and 40.5% in rainfall, along with temperature increases of 3.6 °C and 3.7 °C, were projected under the 'most likely' and 'worst' cases, respectively, for Southern and SW Flatlands West region. Large reductions in rainfall under RCP 8.5 were also projected for Southern and SW Flatlands East by 2090, with 23.4% and 30.9% reductions in rainfall, along with temperature increases of 3.2 °C and 3.5 °C, for the 'most likely' and 'worst' cases, respectively. Little change in rainfall was projected under RCP 8.5 for the Murray Basin under its 'most likely' case, but 3.9 °C increase in temperature was projected for 2090.

By 2050 under RCP 4.5 for the 'most-likely' case, hotter/warmer temperatures and little change in rainfall were projected for Central Slopes, Murray Basin and Southern and SW Flatlands East NRMs, but a drier climate projected for Southern and SW Flatlands West. The 'best' cases projected little change in rainfall for the Murray Basin, Southern and SW Flatlands East and Southern and SW Flatlands West, but projected a wetter climate for the Central Slopes NRM. Drier climates were projected, under RCP 4.5 by 2050, across the Central Slopes and Murray Basin regions for their respective 'worst' cases, with much drier climates projected for Southern and SW Flatlands East and Southern and SW Flatlands West. Under RCP 8.5, a wetter climate was projected for the 'most likely' case across the Murray Basin by 2050, with a 13% increase in rainfall. However, only little change was projected for 2090 across the same NRM, with only 0.6% increase in rainfall projected.

3.2. Climate change effects

Median wheat yields modelled for the sites of Mingenew, Kellerberrin and Salmon Gums within the Southern and SW Flatlands West NRM projected declines of 38%, 26% and 38%, respectively, under the 'most-likely' case for RCP 4.5 by 2090. The 'worst' case projected greater declines of 71%, 80% and 67%, respectively, for these sites. However, there were 15%, 48% and 24% increases in median yield, respectively, across the sites by 2090 (Fig. 3). The 'most-likely' and 'best' cases under RCP 4.5 projected increases in median wheat yields for the Central Slopes and Murray Basin NRMs by 2090. The median yields of Moree and Peak Hill in the Central Slopes NRM increased by 9% and 44% under the 'most-likely' case, respectively, and 20% and 46% under the 'best' case, respectively. However, there were decreases in median yield under the 'worst' case by 51% and 52% for both sites by 2090, respectively. Median wheat yields modelled for Minnipa and Maitland in Southern and SW Flatlands East projected marginal increases under the 'most likely' case of 5% and 2%, respectively. There was a 66% increase of median yield projected for Minnipa under the 'best' case, but a 15% reduction for Maitland, by 2090. In the Murray Basin, the median yield projections for the sites of Bordertown, Charlton and Urana projected increases of 3%, 29% and 4%, respectively under the 'most-likely' case by 2090. Greater increases of 8%, 48% and 32%, respectively, were projected under the 'best' case, but decreases of 41%, 80% and 72%, respectively, were projected under the 'worst' case by 2090.

Median wheat yields declined under RCP 8.5 for the 'most-likely' case across all sites by 2090, with the exception of Urana in the Murray Basin NRM. The greatest declines were projected for Southern and SW Flatlands West, with reductions of 49%, 46% and 41% for Mingenew, Kellerberrin and Salmon Gums by 2090, respectively. Greater declines of 65%, 80% and 71% were projected under the 'worst' case for these sites, respectively. However, there were increases of 23%, 55% and 33% under the 'best' cases for the sites, respectively. The largest declines were projected for the Murray Basin under its 'worst' case by 2090, with median reductions 94%, 100% and 92% for Bordertown, Charlton and Urana, respectively. In contrast, increases of 2%, 77% and 82% in median yield were projected for these sites under their 'best' cases by 2090, respectively. Large increases in median yield were projected for the Central Slopes under the 'best' case, consisting of 87% and 32% for Peak Hill and Moree, respectively. This was contrasted with median reductions of 88% and 74% for these sites, respectively, for their 'worst' cases.

Variability, as estimated by the SD in yields between years, changed from the baseline under all projected RCFs and across most sites for the Year 2090. The largest SD under RCP 4.5 was projected for Urana at 2.46 t/ha under its 'most likely' case. The largest changes in SD under RCP 4.5 were projected under the 'worst' case for Bordertown, with a SD of 1.93 t/ha by 2090, an increase of 0.35 t/ha compared with its baseline (Table 6). The smallest SD under RCP 4.5 was projected for Maitland at 0.7 t/ha under its 'most likely' case. The smallest change in SD under was projected under the 'most-likely' case for Peak Hill, with a SD of 1.96 t/ha projected by 2090, a decrease of 0.03 t/ha compared to its baseline. The largest SD under RCP 8.5 was projected for Urana at 2.24 t/ha under its 'best' case. The largest change in SD was projected under the 'worst' case for Maitland, with SD of 1.59 t/ha by 2090, an increase of 0.79 t/ha comparative to its baseline (Table 7). The smallest SD under RCP 8.5 was projected for Urana at 0.53 t/ha under its 'most likely' case. No change in SD was projected under the 'best' case for Charlton, with a SD of 1.25 t/ha. Variation was most consistent under the RCP's 8.5 'worst' case for Southern and SW Flatlands West, with decreases in SD of 0.50 t/ha, 0.59 t/ha and 0.50 t/ha by 2090 for Mingenew, Kellerberrin and Salomon Gums, respectively (Fig. 3).

4. Discussion

The RCF subset projected a hotter and much drier climate for Southern and SW Flatlands West under its 'most-likely' and 'worst cases'

Table 4
Representative Climate Futures projected under RCP 4.5 for four Natural Resource Management (NRM) regions. Case descriptions are listed against their respective Global Climate Models (GCMs) and the classification for modelled years 2050 and 2090.

NRM	Case for year 2090	GCM	Classification year 2050	Mean temp change (°C)	Rain change (%)	Classification year 2090	Mean temp change (°C)	Rain change (%)
Central Slopes	Best Minimum Temperature increase/ wettest	FGOALS-g2	Warmer-Wetter	+ 1.2	+ 7.8	Warmer-Wetter	+ 1.1	+ 14.5
	Most Likely Mean	FIO-ESM	Hotter-Little Change	+ 1.6	+ 1.3	Hotter-Little Change	+ 2.0	+ 4.4
	Worst Maximum temperature increase/ driest	GFDL-CM3	Hotter-Drier	+ 2.7	− 17.2	Much Hotter-Much Drier	+ 3.6	− 24.6
Murray Basin	Best Minimum Temperature increase/ wettest	GISS-E2-R-CC	Warmer-Little Change	+ 1.0	+ 3.2	Warmer-Little Change	+ 1.3	+ 2.9
	Most Likely Mean	MIROC5	Warmer-Little Change	+ 1.1	+ 3.9	Hotter-Little Change	+ 1.6	− 2.5
	Worst Maximum temperature increase/ driest	GFDL-CM3	Hotter-Drier	+ 1.5	− 6.8	Hotter-Much Drier	+ 2.4	− 25.4
Southern and SW Flatlands East	Best Minimum Temperature increase/ wettest	CNRM-CM5	Warmer-Little Change	+ 1.1	+ 2.5	Hotter-Wetter	+ 1.8	+ 17.4
	Most Likely Mean	GISS-E2-R-CC	Warmer-Little Change	+ 0.8	− 1.4	Warmer-Little Change	+ 1.0	− 1.2
	Worst Maximum temperature increase/ driest	HadGEM2-CC	Warmer-Much Drier	+ 1.4	− 13.9	Hotter-Much Drier	+ 1.6	− 23.5
Southern and SW Flatlands West	Best Minimum Temperature increase/ wettest	CNRM-CM5	Warmer-Little Change	+ 1.4	− 0.9	Hotter-Wetter	+ 1.9	+ 12.7
	Most Likely Mean	MPI-ESM-LR	Warmer-Drier	+ 1.7	− 12.9	Hotter-Much Drier	+ 1.8	− 16.0
	Worst Maximum temperature increase/ driest	GFDL-CM3	Warmer-Much Drier	+ 1.3	− 16.2	Hotter-Much Drier	+ 2.1	− 33.8

Table 5
Representative Climate Futures projected under RCP 8.5 for four Natural Resource Management (NRM) regions. Case descriptions are listed against their respective Global Climate Models (GCMs) and the classification for modelled years 2050 and 2090.

NRM	Case for year 2090	GCM	Classification year 2050	Mean temp (°C)	Rain (%)	Classification year 2090	Mean temp (°C)	Rain (%)
Central Slopes	Best Minimum Temperature increase/wettest	NorESM1-M	Warmer-Little Change	+ 1.5	+ 5.4	Hotter-Much Wetter	+ 2.8	+ 18.4
	Most Likely Mean	MPI-ESM-LR	Hotter-Drier	+ 2.4	− 11.6	Much Hotter-Drier	+ 4.8	− 16.4
	Worst Maximum temperature increase/driest	GFDL-ESM2M	Hotter-Much Drier	+ 2.5	− 29.3	Much Hotter-Much Drier	+ 4.5	− 44.7
Murray Basin	Best Minimum Temperature increase/wettest	MIROC5	Warmer-Little Change	+ 1.4	+ 2.0	Hotter-Wetter	+ 2.9	+ 19
	Most Likely Mean	CESM1-BGC	Hotter-Wetter	+ 1.6	+ 13	Much Hotter-Little Change	+ 3.9	+ 0.6
	Worst Maximum temperature increase/driest	GFDL-ESM2M	Hotter-Much Drier	+ 1.6	− 20.2	Much Hotter-Much Drier	+ 3.5	− 38.5
Southern and SW Flatlands East	Best Minimum Temperature increase/wettest	MIROC5	Warmer-Little Change	+ 1.1	+ 1.8	Hotter-Wetter	2.4	+ 16.8
	Most Likely Mean	ACCESS1–0	Warmer-Drier	+ 1.4	− 11.3	Much Hotter-Much Drier	3.2	− 23.4
	Worst Maximum temperature increase/driest	CMCC-CMS	Warmer-Drier	+ 1.4	− 2.5	Much Hotter-Much Drier	3.5	− 30.9
Southern and SW Flatlands West	Best Minimum Temperature increase/wettest	FGOALS-g2	Warmer-Drier	+ 1.3	− 11	Hotter-Little Change	+ 2.6	+ 16
	Most Likely Mean	HadGEM2-CC	Hotter-Much Drier	+ 1.9	− 27.2	Much Hotter-Much Drier	+ 3.6	− 30.0
	Worst Maximum temperature increase/driest	MPI-ESM-LR	Hotter-Drier	+ 1.7	− 7.1	Much Hotter-Much Drier	+ 3.7	− 40.5

Table 6
Standard Deviation in wheat yield for study sites under RCP4.5.

	Baseline	Year 2050			Year 2090		
		Best case	Most likely	Worst case	Best case	Most likely	Worst case
Mingenew	1.27	1.33	1.46	1.18	1.12	1.50	0.80
Kellerberrin	1.25	1.38	1.25	0.85	1.45	1.05	0.51
Salmon Gums	1.14	1.32	1.04	0.98	1.33	1.21	0.85
Minnipa	1.44	1.42	1.42	1.23	1.26	1.56	1.11
Maitland	0.80	0.65	0.74	0.97	0.70	0.70	1.01
Bordertown	1.58	1.50	1.44	1.95	1.50	1.41	1.93
Charlton	1.73	1.86	1.84	1.73	1.87	1.95	1.61
Urana	2.14	2.28	2.39	1.59	2.44	2.46	1.15
Peak Hill	1.99	1.96	1.95	1.60	1.92	1.96	1.81
Moree	1.36	1.22	1.28	1.34	1.18	1.22	1.58

under RCP 4.5 and a much hotter and much drier climate under RCP 8.5. These projections resulted in overall declines for wheat yield, ranging from 26% under RCP 4.5 to 80% under RCP 8.5 by 2090. Rainfall change presented the strongest signal to change in wheat yield, which was consistent with other studies (Hochman et al., 2017; Luo et al., 2005; Anwar et al., 2007; Hunt and Kirkegaard, 2012). For the Southern and SW Flatlands West region, the analysis pointed to the need for specific adaptations under drier and much hotter climates. In contrast, little change in rainfall, but warmer temperatures, were projected for Central Slopes, Murray Basin and Southern and SW Flatlands East for its 'most-likely' case under RCP 4.5, indicating specific adaptations towards warmer climates for those regions.

A much hotter, but little change in rainfall was projected under the 'most-likely' RCP 8.5 case for Murray Basin. This resulted in a range of impacts, with an increase in median yield for Urana, marginal decrease for Charlton and a decline for Bordertown. The added CO_2 fertilisation under RCP 8.5 improved yields for Urana, but the impact of higher temperatures (+ 3.9 °C) negated this factor for Bordertown. However, the added benefit of CO_2 fertilisation needs to be treated conservatively, because APSIM has been reported to overestimate the effect of CO_2 fertilisation (O'Leary et al., 2015). All regions were projected to have increased rainfall for the 'best' cases, but hotter temperatures exceeding 2 °C by 2090. The higher rainfall and added CO_2 fertilisation increased yields for all sites, with the exception of Maitland, which projected a decline of 8% by 2090. Again, higher temperatures negated the benefits of added CO_2 fertilisation and increased rainfall.

The analysis of SD included additional information, focusing on the impact of projected climate change, as well as the change in variability between years. Low SD sites, such as Maitland, indicated more predictable yields. High SD sites, such as Urana, indicated less predictable yield year to year. Therefore, Maitland appeared to require less adaptation than Urana. From these results, projections favoured farming at Maitland comparative with Urana. However, the maximum and minimum yields need to be taken into account for these sites, because sites with a high SD may be favourable if the rewards in a good year make up for the bad year. Maitland was impacted more negatively under its worst case for RCP 8.5, in comparison with RCP 4.5, where yield declined and became more variable from year to year. However, variability decreased along with yield for all sites under RCP8.5 and its respective 'worst' cases, with Urana presenting the greatest reduction in variability of 1.61 t/ha.

Where variability in yield is higher, the risk of maladaptation can be greater. This can involve either over or under adaptation to potential climate change and a misalignment between policy and practice, leading to unintended management responses or the provision of perverse incentives (Howden et al., 2010). Improving precision and managing known risks to reduce existing deficits in production performance may be of prime importance (Vermeulen et al., 2013). The crucial point is that not only do future climates present the challenge of likely overall changes in yields, but also the even trickier challenge of far greater variance in productivity between years, making it difficult for farmers and policy makers to plan and invest (Ghahramani et al., 2015).

This raises difficult questions for farmers about their best enterprise mix and even location. Some may choose to crop in a more opportunistic mode, focusing on other enterprises, such as grazing when seasonal conditions are projected to be unfavourable for cropping, and gearing up for a profitable 'bumper crop' when the signals are encouraging. Even so, for such an adaptation strategy to be successful, not only do seasonal forecasts have to be reliable, but factors, such as soil condition, the relative effect of climate change on other enterprises, fluctuations in commodity prices and the security of regional support for certain enterprises (e.g. provision of grain silos), as well as farmers' workload and other goals, all demand careful consideration. Making decisions in the context of such complexity is a growing challenge (Kingwell, 2011; McGuckian and Rickards, 2011), pointing to the need for not only more whole farm analysis (eg Nelson et al., 2010a, 2010b), but also real options analysis (eg Sanderson et al., 2016) that better

Table 7
Standard Deviation in wheat yield for study sites under RCP8.5.

	Baseline	Year 2050			Year 2090		
RCP8.5		Best case	Most likely	Worst case	Best case	Most likely	Worst case
Mingenew	1.27	1.55	1.34	1.36	1.60	1.22	0.77
Kellerberrin	1.25	1.19	0.98	1.08	1.64	0.96	0.66
Salmon Gums	1.14	1.18	1.17	1.17	1.42	1.06	0.64
Minnipa	1.44	1.50	1.28	1.48	1.19	1.10	0.89
Maitland	0.80	0.69	1.03	0.67	0.73	1.00	1.59
Bordertown	1.58	1.61	1.18	1.80	0.76	1.37	1.49
Charlton	1.73	1.92	1.77	1.48	1.73	1.84	0.60
Urana	2.14	2.28	2.35	1.16	2.24	2.22	0.53
Peak Hill	1.99	1.98	2.03	1.37	1.76	1.85	1.00
Moree	1.36	1.32	1.51	1.36	0.83	1.23	1.22

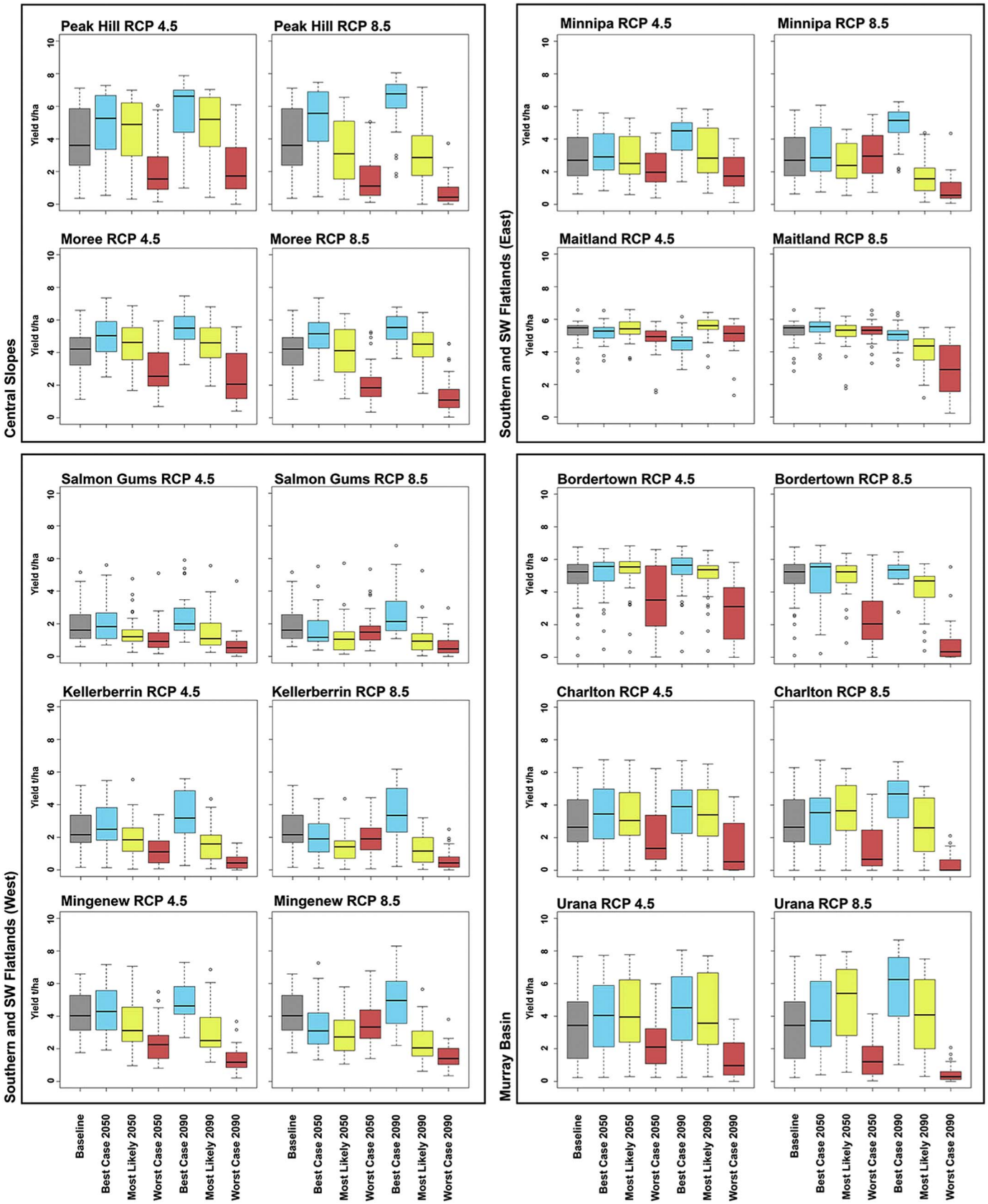

Fig. 3. Box and whisker plots of projected changes to wheat yield for the study sites. The grey box represents the baseline climate 1980 to 2010. The blue, yellow and red boxes represent the low (best case), mean (most likely) and high (worst) climate change cases, respectively. Box plots represent the 25th, 50th and 75th percentile, with the 10th and 90th percentile in the whiskers for the 31 repeated-years. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

accommodate uncertainty. Environmental monitoring, continual adjustment to emerging conditions and periodic evaluation – of the sort potentially encouraged by big data capabilities – are also important elements of managing under uncertainty. The specific adaptations possible in different situations is an important area for action research.

The upshot for adaptation is that greater variance in climate and possible crop yields requires widespread incremental changes, such as new crop variety maturity type, level of nitrogen fertiliser or sowing date (Ghahramani et al., 2015). However, these incremental adaptations may not be adequate in some of the regions modelled. Instead, the "package" of adaptations a given farmer chooses is likely, at least in some regions, to have to include more systemic adaptations, such as a change in enterprise mix, or transformational adaptation, such as a shift out of cropping, or an existing spatial region altogether (Rickards and Howden, 2012; Park et al., 2012). While perhaps an unpalatable topic with farmers (Robertson and Murray-Prior, 2016), such changes need to be discussed, given that the decisions involved can take a long time to reach and implement (Stafford Smith et al., 2011), require dialogue with others in the region or local community and can be mentally and emotionally taxing (Ellis and Albrecht, 2017). Cross-regional conversations may be needed, because producers singly or collectively move towards taking better advantage of differences in climatic conditions between regions over short or long-term time scales, injecting a new degree of mobility into agricultural production that policy makers need to think through.

The benefits of using the RCF method to model projected climate change on agricultural productivity allowed for greater insight into the challenges surrounding adaptation through a more locally representative subset of GCMs, capturing projected variability across farming regions (Whetton et al., 2012; Clarke et al., 2011). Other studies have highlighted these benefits. Ruane and McDermid (2017) argue that a GCM subset was cognizant of potential outliers that may be evidence of substantial biases, whereby the hottest and least warm, driest and wettest cases were included in the analysis. Furthermore, the selection of GCMs was connected to weights that denoted the ensemble-based probability of GCM projections similar to each within the subset. Similar to the GCM selection used by Ruane and McDermid (2017), this study used a statistical method of selection based on climate groups (i.e. hot/dry, hot/wet) that provided a representative subset and avoided excessive computations and modelling involved with using the full suite of GCMs. However, the RCF method went further, where it applied GCM selection at the regional level, involving the regional skill of a GCM and a statistical multi-variate ranking technique in relation to selected climate variables. In this context, comparisons can be made between specific agricultural regions in Australia. More work is needed to explore how scenarios in one region relate to those in other regions and thus to the overall situation at larger scales, including the nation (Blanco et al., 2017). Furthermore, the limitation of the RCF method using single years in its calculations requires further work across multiple years in succession and the year-to-year variation modelled within each GCM.

A key question is whether there tends to be commonalities (e.g. concurrent worst case scenarios) or differences between regions in the sort of climate scenarios they are likely to experience. This will colour the indirect effects of climate change that farmers experience via distant impacts on their supply chains, infrastructure networks and markets they rely on. It will also shape what spatial adaptation options are open to them (i.e. farm relocation or supply chain reconfiguration) and the competitive advantage of and synergies between different regions, as mediated by market shifts and the regional and other policies that governments implement (Plummer et al., 2017). This means that a multi-scale approach is needed in planning agricultural adaptation (Blanco et al., 2017).

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